Zero-shot classification of ECG signals using a CLIP-based model

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Abstract

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# Introduction

According to the World Heart Federation (WHF), a leader in global cardiovascular health, among other reports from leading clinicians, researchers and institutions, cardiovascular diseases (CVDs) are a leading cause of mortality worldwide [17; 22; 25; 36]. In the United States, the Center for Disease Control (CDC) estimates that the annual total cost associated with CVD-related treatment and mortality is approximately $219 billion dollars (USD) per year [18; 21]. Given the financial and socioeconomic burdens of CVDs, it is essential that individuals receive timely and accurate medical care for the diagnosis, treatment, and ongoing care of CVDs.

An electrocardiogram (ECG) remains the medical standard and benchmark for the identification and diagnosis of CVDs with more than 300 million ECGs being performed globally [7]. In general, ECGs measure the changes in electrical membrane potential of the heart across different directions of the body and are often referred to as leads with a 12-lead ECG report being the most common type of report [14; 29]. Once an ECG report is available, it is ready to be analyzed by a licensed medical professional such as a cardiologist or an auxiliary medical professional.

However, it is important to note that even today, interpreting and analyzing ECG reports remains a highly complex and time-consuming process for medical professionals [11]. Not only are ECG reports manually annotated but the individual analyzing the ECG report must possess a high degree of technical skills and a vast understanding of topics such as cardiac anatomy, electrophysiology, pattern recognition, coronary distribution, and pathophysiology to perform correctly and accurately [11]. In one systematic literature review by Cook et al., it was found that medical professionals, such as cardiologists, across levels of education experienced challenges in providing a correct diagnosis for an ECG report with correct interpretation accuracy ranging from 49% to 92% and with a median interpretation accuracy of 57% [11]. In the same systematic literature review, it was also found that medical professionals who received continuing education and training related to ECG interpretation and analysis, did improve their ability to correctly provide a diagnosis for an ECG report with a median accuracy of 67%, suggesting that ongoing training for medical professions can play an important role in providing correct diagnoses [11].

Seeing the challenge that medical professionals

# Related Works

# Materials and Methodology

# Results

# Discussion

# References

1. A large-scale multi-label 12-lead electrocardiogram database with standardized diagnostic statements. / H. Liu [et al.] // Sci Data. — 2022. — Vol. 9. — DOI: https://doi.org/10.1038/s41597-022-01403-5.

2. Ahsan M.M. Luna A.S. S. Z. Machine-Learning-Based Disease Diagnosis: A Comprehensive Review // Healthcare (Basel, Switzerland). — 2022. — Vol. 10, no. 3. — P. 1461–1471. — PMID: 35327018.

3. An Open Access Database for Evaluating theAlgorithms of Electrocardiogram Rhythm andMorphology Abnormality Detection / F. Liu [et al.]. — 2018. — Journal of Medical Imaging and Health Informatics.

4. Artificial intelligence-enhanced electrocardiography in cardiovascular disease management / C. K. Siontis [et al.] // Nature Reviews Cardiology. — 2021. — Vol. 18. — P. 465–478. — DOI: 10.1038/s41569-020- 00503-2.

5. Automatic multilabel electrocardiogram diagnosis of heart rhythm or conduction abnormalities with deep learning: a cohort study / H. Zhu [et al.] // The Lancet. Digital health. — 2020. — Vol. 2, no. 7. — P. 348–357. — DOI: 10.1016/S2589-7500(20)30107-2.

6. Automatic Premature Ventricular Contraction Detection Using Deep Metric Learning and KNN / J. Yu [et al.] // Biosensors. — 2021. — Vol. 11, no. 3. — DOI: ttps://doi.org/10.3390/bios11030069.

7. Chhabra L. S. Y. Electrocardiogram // StatPearls [Internet]. — 2023.

8. Classification of 12-lead ECGs: the PhysioNet/Computing in Cardiology Challenge 2020 / P. Alday [et al.] // Institute of Physics and Engineering in Medicine. — 2020. — Vol. 41, no. 12. — DOI: <https://doi.org/10.1088/1361-6579/abc960>.

9. CLIP in Medical Imaging: A Comprehensive Survey / Z. Zhao [et al.] // arXiv. — 2023. — DOI: arXiv:2312.07353.

10. CLIP: Connecting text and images / A. Radford [et al.]. — 2021.

11. Cook A.D. Oh S.Y. P. V. Accuracy of Physicians’ Electrocardiogram Interpretations: A Systematic Review and Meta-analysis // JAMA internal medicine. — 2020. — Vol. 180, no. 11. — P. 1461–1471. — PMID: 32986084.

12. Diagnostic statement dictionary / H. Liu [et al.]. — 05/2022. — DOI: 10.6084/m9.figshare.17912507. v1. — URL: https://springernature.figshare.com/articles/dataset/diagnostic\_statement\_ dictionary/17912507 ; 12-lead electrocardiogram; ECG; Multi-label; ECG abnormalities. Figshare.

13. ECG records / H. Liu [et al.]. — 2022. — DOI: 10 . 6084 / m9 . figshare . 17912444 . v1. — URL: https://doi.org/10.6084/m9.figshare.17912444.v1. Figshare.

14. Electrocardiography: A Technologist’s Guide to Interpretation / C. Tso [et al.] // Journal of Nuclear Medicine Technology. — 2015. — Vol. 43, no. 4. — P. 247–252. — DOI: 10.2967/jnmt.115.163501.

15. ETP: LEARNING TRANSFERABLE ECG REPRESENTATIONS VIA ECG-TEXT PRE-TRAINING / C. Liu [et al.] // arXiv. — 2023. — DOI: arXiv:2309.07145v1.

16. Frozen Language Model Helps ECG Zero-Shot Learning / J. Li [et al.] // arXiv. — 2023. — DOI: arXiv:2303.12311.

17. Global, regional, and national age-sex specific mortality for 264 causes of death, 1980-2016: a systematic analysis for the Global Burden of Disease Study 2016 // THE LANCET. — 2017. — Vol. 390, 10100. — P. 1151–1210. — PMID: 28919116.

18. Heart Disease and Heart Attack. — Centers for Disease Control, Prevention, 2021. — URL: https: //www.cdc.gov/policy/polaris/healthtopics/heartdisease/index.html ; Accessed: 2024-01-15. [Electronic resource].

19. KecNet: A Light Neural Network for Arrhythmia Classification Based on Knowledge Reinforcement / P. Lu [et al.] // Journal of Healthcare Engineering. — 2021. — DOI: https://doi.org/10.1155/2021/ 6684954. — eprint: 6684954.

20. Learning Transferable Visual Models From Natural Language Supervision / A. Radford [et al.] // Proceedings of Machine Learning Research. — 2021. — Vol. 139. — P. 8748–8763.

21. Lui J.N. et al. Impact of New Cardiovascular Events on Quality of Life and Hospital Costs in People With Cardiovascular Disease in the United Kingdom and United States // Journal of the American Heart Association. — 2023. — Vol. 12, no. 19. — ISSN e030766. — DOI: 10.1161/JAHA.123.030766. — URL: <https://www.ahajournals.org/doi/10.1161/JAHA.123.030766>.

22. Machine learning-based detection of cardiovascular disease using ECG signals: performance vs. complexity / H. Pham [et al.] // Front. Cardiovasc. Med. — 2023. — Vol. 10. — DOI: 10.3389/fcvm.2023. 1229743. 20

23. Mamun K.R.M.M. E. T. AI-Enabled Electrocardiogram Analysis for Disease Diagnosis // Applied System Innovation. — 2023. — Vol. 6, no. 5. — DOI: <https://doi.org/10.3390/asi6050095>.

24. Mapping from Chinese ECG statements to AHA codes / H. Liu [et al.]. — 05/2022. — DOI: 10.6084/ m9.figshare.19738468.v1. — URL: https://springernature.figshare.com/articles/dataset/ Mapping\_from\_Chinese\_ECG\_statements\_to\_AHA\_codes/19738468 ; 12-lead electrocardiogram; ECG; Multi-label; ECG abnormalities. Figshare.

25. Mensah A.G. Roth A.G. F. V. The Global Burden of Cardiovascular Diseases and Risk Factors: 2020 and Beyond // Journal of the American College of Cardiology. — 2019. — Vol. 74, no. 20. — P. 2529–2532. — ISSN 0735-1097. — DOI: 10.1016/j.jacc.2019.10.009. — URL: https://www.sciencedirect.com/ science/article/pii/S0735109719379288.

26. OpenStax College Anatomy & Physiology //. — OpenStax College, 2013. — URL: https://commons. wikimedia.org/w/index.php?curid=30148227.

27. PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals / A. Goldberger [et al.] // Circulation [Online]. — 2000. — Vol. 101, no. 23. — P. 215–220.

28. Pollock D., Makaryus N. Physiology, Cardiac Cycle // StatPearls. — 2022.

29. Prutkin M. ECG tutorial: Basic principles of ECG analysis // UpToDate. — 2023.

30. PTB-XL, a large publicly available electrocardiography dataset / P. Wagner [et al.]. — 2020. — URL: https://www.nature.com/articles/s41597-020-0495-6. Scientific Data.

31. Publicly Available Clinical BERT Embeddings / E. Alsentzer [et al.] // Proceedings of the 2nd Clinical Natural Language Processing Workshop. — Association for Computational Linguistics, 2019. — P. 72– 78. — DOI: 10.18653/v1/W19-1909. — URL: <https://www.aclweb.org/anthology/W19-1909>.

32. Scikit-learn: Machine Learning in Python / F. Pedregosa [et al.] // Journal of Machine Learning Research. — 2011. — Vol. 12. — P. 2825–2830.

33. State-of-the-Art Deep Learning Methods on Electrocardiogram Data: Systematic Review / G. Petmezas [et al.] // JMIR Medical Informatics. — 2022. — Vol. 10, no. 8. — PMID: 35327018.

34. The attributes of ECG records / H. Liu [et al.]. — 2022. — DOI: 10.6084/m9.figshare.17912441.v1. — URL: https://doi.org/10.6084/m9.figshare.17912441.v1. Figshare.

35. Will Two Do? Varying Dimensions in Electrocardiography: The PhysioNet/Computing in Cardiology Challenge 2021 / M. Reyna [et al.] // PhysioNet. — 2022. — DOI: <https://doi.org/10.13026/34va7q14>.

36. World Heart Report 2023. — World Heart Federation, 2023. — URL: https : / / world - heart - federation.org/resource/world-heart-report-2023/ ; Accessed: 2023-10-15. [Electronic resource].

37. Yanowitz G. 1. The Standard 12 Lead ECG // ECG LEARNING CENTER. —.

38. Zero-Shot Classification. — 2023. — URL: https : / / huggingface . co / tasks / zero - shot - classification